Data-driven indicators for the detection and prediction of stuck-pipe events in oil&gas drilling operations

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Abstract

Stuck-pipe phenomena can have disastrous effects on drilling performance, with outcomes that can range from time delays to loss of expensive machinery. In this work, we develop three indicators based on mudlog data, which aim to detect three different physical phenomena associated with the insurgence of a sticking. In particular, two indices target respectively the detection of translational and rotational motion issues, while the third index concerns the wellbore pressure. A statistical model that relates these features to documented stuck-pipe events is then developed using advanced machine learning tools. The resulting model takes the form of a depth-based map of the risk of incurring into a stuck-pipe, updated in real-time. Preliminary experimental results on the available dataset indicate that the use of the proposed model and indicators can help mitigate the stuck-pipe issue.

Keywords: Oil&Gas, Drilling, Stuck-pipe, Detection, Prediction, Data-driven methods, Rare events.

1. Introduction

Drilling is a complex process that consists in boring a hole (which can be several thousands of meters long) in order to create a well for oil (or gas) production. The drill bit is mounted on the bottom hole assembly (BHA), which is located at the end of a pipe that extends from the rig to the bottom of the well. The drill pipe is rotated by the surface machinery on the drilling rig and, as the hole depth increases, its length is increased by assembling further pipe segments from the top. Typically, the added pipe elements (called stands) consist of two or three preassembled segments of drill pipe. Conversely, when the BHA needs to be extracted from the well (tripping out operation), *e.g.*, because the drill bit needs to be replaced, the stands are disconnected one by one and stocked as they emerge. A stand can be made of drill collars as well (drill collars are heavier pipes used to provide weight on the bit to facilitate drilling).

The gravity that acts on the drill pipe and in particular on the collars provides the downward force necessary for the bit to break the rock. Using the rig's hoist and rotation system, the driller lowers the drill string on the bottom of the wellbore and then controls the weight applied to the bit. The drill bit crushes the rock into cuttings, which are removed from the bottom and mechanically transported up towards the rig by way of a special drilling mud. The latter is pumped down the pipe and returns to the rig by passing through the annulus, *i.e.*, the space between the pipe and the wall of the borehole. Besides carrying the drilled cuttings from the hole bottom up to the rig level, the mud has other functions, *i.e.*, to cool down and lubricate the bit and –most importantly– to keep the borehole from falling down. Indeed, the hole is stable as long as the hydrostatic pressure of the mud is greater than the pore pressure. Otherwise, the gas flows upwards (well flowing/kick), and a blow out may occur. If the mud hydrostatic pressure is too large, it may cause fractures in the formation, with consequent mud losses.

The drilling is periodically interrupted to fit the wall of the newly drilled portion of the well with a protective casing, for mechanical support and insulation. Various casings with a progressively smaller diameter are generally used, starting, *e.g.*, from an initial hole with a diameter of 70 cm down to 10 cm. The drilling process is a sequence of different operations, including drilling, reaming (passing repeatedly along already drilled portions of the hole to clean it), stand changing, casing, and tripping (extracting or reinserting the whole pipe, *e.g.*, to replace the BHA).

The drilling process may be slowed down or jeopardized by various adverse events, due to well problems (such as circulation losses, stickings, fluid influx, etc.), rig failures, downhole or surface equipment failures, etc. In particular, the occurrence of sticking (or stuck-pipe) phenomena may ultimately result in catastrophic outcomes entailing pipe breakage, the loss of expensive downhole equipment, and a considerable delay in drilling operations. A sticking can be caused by various different physical phenomena: it occurs when the vertical motion or rotation of the drilling pipe is impeded. Various actions can be exerted by the operator in an attempt to unblock the BHA, at the cost of a delay in drilling. In the most unfortunate cases, the BHA cannot be freed and must be abandoned, and the drilling is later resumed along a different trajectory.

Timely prediction of sticking events is therefore considered a primary necessity to assist the drilling team in the decision-making process, so that appropriate countermeasures can be put in effect before the situation slips out of hand. However, this problem is very challenging due to the hybrid nature of the drilling process (which consists of different activities), the variability of geological conditions, the combined occurrence of adverse events, and the availability of indirect sources of information regarding the occurrence of stickings under form of measurements associated with the operation of surface equipment.

Numerous works have appeared in the recent scientific literature concerning the application of machine learning methods to data analysis tasks related to the drilling process. The work of Roar Nybø systematically combines the use of physical models of the wellbore and drilling process with machine learning techniques to detect and anticipate anomalies in real-time during drilling operations. For example, in (Nybø, 2009) the attention is devoted to the anticipation of kicks (by monitoring the mud return rate) and stickings, with specific emphasis on reducing false alarms. In (Gulsrud et al., 2009) a model is used to anticipate poor hole cleaning conditions that may cause sticking events. They suggest the use of the Bottom Hole Pressure (BHP) (or alternatively the Stand Pipe Pressure (SPP), if the BHP is not available) and the TQA (TorQue Average) as inputs for the detection scheme. In particular, the skewness of the BHP and the normalized standard deviation of the TQA are used.[1] They claim that a sticking is characterized by one-sided positive spikes of the skewness of the BHP and large oscillations of the TQA, so that the product of the two indicators may provide a good indicator. Diagnostics are calculated over a moving time window of 30 minutes.

[1]The skewness measures the asymmetry of the probability distribution, whereas the standard deviation indicates the level of oscillation of the signal.

Solberg (2012) discusses an automatic procedure to detect hardness during drilling (drillability is the inverse of hardness). The method employs a simplified version of the penetration rate equation proposed by Bourgoyne et al. (1986). It only considers the variables WOB (Weight On Bit), RPM (rotary speed measured in Rounds Per Minute), and ROP (Rate Of Penetration). The outcome of the method is a plot of hardness variation against depth, which can be used to optimize the setting of the machinery by suitably matching the bit and reamer aggressiveness.

Many works focus on the prediction and optimization of the rate of penetration (ROP) using machine learning methods, see *e.g.*, (Sui et al., 2013), (Wallace et al., 2015), (Hegde et al., 2015), (Hegde and Gray, 2017). Others consider the task of predicting the bottom hole pressure, see *e.g.*, (Sui et al., 2011), (Gola et al., 2012), (Sui et al., 2012). In (Roberts et al., 2016) the task of detecting and recognizing a kick is studied from a cognitive point of view; a decision tree is designed to aid the driller in the detection and reaction to the kick. In (Nybo and Sui, 2014) a clustering method is employed to recognize anomalies in the mud log data. Finally, some works are concerned with the prediction of stick-slip phenomena as well, see (Efteland et al., 2015).

Regarding specifically stuck-pipe prediction, the recent survey by Al Dushaishi et al. (2020) covers various methods in the literature, most of which are based on neural networks and proposes its own, which uses classification trees. These methods generally address the detection of stuck-pipe events, rather than their prediction with sufficient anticipation to enact avoidance strategies. Furthermore, since they are not designed for real-time usage, they employ a much larger set of features compared to our study, including also features that are not commonly available in the field in real-time.

In this work, we first develop three data driven indicators, associated with different physical phenomena, aimed at recognizing stickings and their related precursor events. These indicators can be interpreted as virtual or soft sensors of different non-directly measurable drilling problems associated with stickings. Soft sensors are become increasingly important in the monitoring and control of industrial processes Jiang et al. (2020). In particular, the first two indicators address the mechanical phenomena indicating the difficulty to move the BHA along the borehole direction or to rotate it. The third indicator aims instead at spotting unexpected pressure surges, which may indicate, *e.g.*, the formation of pack-off in the bottom section. We then use these indicators to build a statistical model capable of anticipating the occurrence of stuck-pipe events. This model provides an assessment of the level of risk associated as a function of the borehole depth, and is accordingly denoted *wellbore status model*.

Various data are available for the computation of the indicators, namely timelog data annotated by the drilling operators, mudlog data collecting measurements from the surface equipment, and lithology data. Further measurements can be taken at the bottom of the well using additional sensors at the BHA, but these data are seldom available and are not in real-time (they cannot be used for online processing).

Timelog data are crucial as they contain the operators' assessments regarding all the issues encountered while drilling and the processing of these data provides the ground truth for detecting the sticking events. Unfortunately, the consistency of timelogs is sometimes questionable, due to the subjectivity of the operators' evaluations. As a consequence, minor or brief sticking problems may not be reported as such and other well problems may be mistakenly reported as sticking events. Furthermore, annotations are not precisely aligned in time with data, as required for the data processing task. The main and more reliable source of information on the drilling process is currently represented by the mudlog data, which are accordingly used in the following for the development of the indicators and the wellbore status model. Finally, while potentially useful, the lithology data are not employed in this study, since they are typically available only *a posteriori* (the lithology type corresponding to each depth section is determined in practice by examining the mud and cuttings produced during drilling activities).

The main features of the proposed approach are summarized below:

- Specific stuck-pipe related features (the three indicators) are constructed based on data. These indicators are valuable on their own in that they point out specific drilling issues to the human operator.

- Only a few mudlog signals are employed to build these indicators, that are typically available on-line to the driller (many variables used in other works are not).

- An artificial alarm signal that increases when approaching a sticking is used as a target in the learning process.

- The wellbore status model works both on a time scale and on a depth scale. Indeed, it sometimes occurs that a problem builds up at a certain depth of the borehole, and the information collected during the various times the BHA passes in that specific section can be used to anticipate a sticking there, even at a much later time.

- The model provides at each time a status evaluation of the whole borehole, indicating different levels of risk at each depth. This gives a precious real-time feedback to the driller regarding portions of the borehole that require particular care and attention.
- The model operates in real-time, *i.e.* processes the mudlog data with a delay of few minutes, a time that is much shorter than the typical sticking build-up time. It can also be updated at a relatively fast rate (retraining can be completed in a matter of few minutes), although our experience indicates that this is not necessary, as the model changes slowly over time.

The remainder of the paper is structured as follows. Section 2 provides a detailed description of the available mudlog signals, while Section 3 discusses their behavior in relation to stuck-pipe conditions. The three proposed indicators are introduced in Sections 4-6, and finally the prediction model is sketched in Section 7. Some concluding remarks end the paper.

For the reader's convenience a list of acronyms used throughout the paper is provided in Table 1.

Table 1: List of acronyms

BHA	Bottom Hole Assembly
BHP	Bottom Hole Pressure
BPOS	Block POSition
DBTM	Depth of the BiT Measured
DBTV	Depth of the BiT Vertical
DMEA	Depth of the hole MEAsured
DVER	Depth of the hole VERtical
HKLA	HooK Load Average
MDIA (MDOA)	Mud Density at the Input (Output) Average
MFIA (MFOA)	Mud Flow at the Input (Output) Average
ROP (ROPA)	Rate Of Penetration (ROP Average)
RPM (RPMA)	Revolutions Per Minute (RPM Average)
SPP (SPPA)	Stand Pipe Pressure (SPP Average)
SPMT	total pump stroke rate
STKC	pump STroKe Count
TQA	TorQue Average
TRPM	Total RPM
WOB (WOBA)	Weight On Bit (WOB Average)

2. Mudlog data description and analysis

Mudlog data report the measurements of several variables[2] related to the drilling process sampled every 5 seconds (the variables with suffix ‘A’ are averaged over the sampling period). In the mudlog datasets considered in this study, the sampling is not always regularly spaced every 5 seconds, as isolated samples and, occasionally, a number of consecutive samples are missing.

Various variables related to drilling depth are available. DBTM (Depth of the BiT - Measured) and DBTV (Depth of the BiT - Vertical) are measurements of the bit depth, the first along the drilling direction, the second in the vertical direction. The measured depth DMEA (Depth of the hole - MEAsured), together with its vertical companion DVER (Depth of the hole - VERtical), indicate the hole depth and they are (generally) non-increasing

[2]Some variables are actually not measured, but computed from other measurements.

curves. Occasionally, the DBTM displays abrupt jumps (up to thousands of meters), mostly upwards and especially during tripping operations. These events typically correspond to manual resets of the DBTM after the mounting of a casing. DBTM displays a characteristic pattern during the sticking episodes, in which it shows small high-frequency oscillations, possibly related to the operator's attempts to unblock the system.

Another subset of mudlog variables relates to the drilling process. For example, the BPOS (Block POSition) measures the position (height) of the traveling block, which supports the drill pipe. BPOS has a characteristic oscillatory behavior during the sticking phase, possibly related to the operator's attempts to unblock the system. After a sticking the BPOS variations slow down and, after a few seconds, the variable remains fixed. The TQA is a measure of the rotary torque applied to the drill string (taken at the rotary table or at the top drive motor cable). Large TQA values generally indicate some difficulties in the drilling process related to the presence of some obstacles to the rotation of the drill pipe and occasionally to the insurgence of sticking. However, high TQA spikes are experienced also during legitimate operations (*e.g.*, mounting of stands). During drilling operations the average value of TQA is non-zero. It is normally zero when the BHA does not rotate. RPMA (RPM Average) and TRPM (Total RPM, measured downhole) are variables related to the rotary speed, the latter accounting also for the additional rotation applied to the BHA. RPMA is often equal to zero during tripping operations, but it is also expected to be zero when the BHA is stuck and cannot rotate. The ROPA (ROP Average) marks the actual drilling phase. The HKLA (HooK Load Average) measures the tension on the cable from the drawworks. HKLA is expected to increase (with no variations of DBTM) at sticking events. The WOBA (WOB Average) is the amount of downward force exerted on the drill bit and results from all the components of the drillstring (*e.g.*, drill collars). To accurately control the amount of force applied to the drill bit, the driller carefully monitors the weight measured at the surface while the bit is just off the bottom of the wellbore. When the drillstring is lowered and the bit touches the bottom, more weight is applied to the bit (and less is measured as hanging at the surface). The WOBA is set by the operator to match the characteristics of the formation that must be drilled. Notice that the WOBA is *calculated* from HKLA, RPMA, the drillstring weight, and mud flow variables (hydrostatic force). As such, it is considered reliable only during drilling. The WOBA is expected to be zero during tripping time and its values are different from zero in the drilling phase (*i.e.*, when DBTM increases with DMEA) or during trips in open hole when the BHA faces tight spots. The WOBA increases in the drilling before the sticking occurs, at the sticking depth.

Various mudlog variables are related to the mud flow regulation, such as MDIA/MDOA (Mud Density at the Input/Output - Average) and MFIA/MFOA (Mud Flow at the Input/Output - Average). Under normal conditions of the well, MFOA should be equal to MFIA. No significant variation of the MDIA/MDOA variables is observed near sticking events and, consequently, these variables have been neglected in the sequel. When there is a sticking event, the MFOA can drop to zero. The same situation also occurs in the case od circulation losses. A set of related variables concerns the pump regulation (*e.g.*, the pump STroKe Count, STKC, or the total pump stroke rate SPMT) and pressure measurements. The SPPA (Stand Pipe Pressure Average) measures the pressure of the mud on the stand pipe.

The mudlog data used in the project display several critical aspects (missing samples, timezones, outliers, non-uniformity of signal units, ranges and dynamics across wells, etc.), so that a great deal of effort was spent in data cleaning and preprocessing, to make them ready for the application of machine learning methods.

2.1. Mud log variables in nominal conditions: drilling

An example of normal behavior during drilling is shown in Figures 1-2. The period from 17:20 to 19:20, approximately, corresponds to the drilling of a complete stand (42 m). This operation may take anything from one to 10 hours. The actual drilling of the stand takes place from 17:40 to 19:13 (time interval where the ROPA, not shown due to lack of space, is greater than 0), while the 20 minute periods immediately before and after the drilling, where RPMA, HKLA and SPPA drop to a low value, correspond to the stand change operations. During drilling, the rotary speed (RPMA) is kept constant at a set-point defined by the operator. Occasional drops (*e.g.* around 20:00 or slightly after 21:00) in combination with TQA surges indicate some small tight spots. After 19:20 a reaming-backreaming operation is carried out (ending at 19:24), to clean up the hole: the BHA (see BPOS and DBTM) is moved up by a stand length while continuing to apply rotation and then it is lowered back to the bottom of the hole again. Notice the reduced strain during these operations (TQA is typically much lower than during drilling).

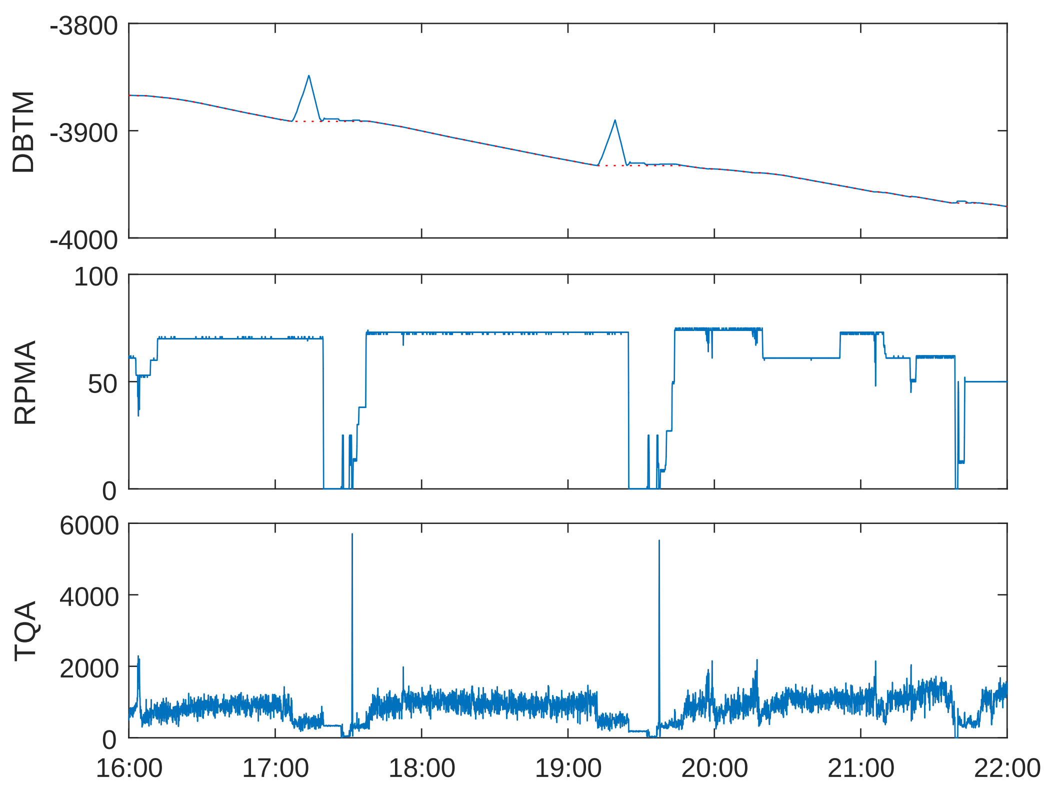

Figure 1: Drilling example 1. From top to bottom: DBTM (blue) and DMEA (red), RPMA, TQA.

The rotation is stopped immediately after (RPMA goes to 0) to initiate the stand change.

During the latter operation, a new stand is mounted on top of the previous one. First, the rotation (and the mud flow) is stopped (RPMA=0), with BPOS at a constant value of about 10 m. Then, at some point, the drill string is clamped (HKLA drops to around 40 tons). Then the moving block is disengaged and lifted (BPOS rapidly goes to 50 m) and the new stand is mounted and lowered (BPOS decreases slowly). After about half a meter the new stand fits in the rest of the stand pipe. The connection is tightened by the rotation applied to the new stand, while the rest of the stand pipe is still clamped. As a result, a TQA impulse is recorded (*e.g.* at 17:30). Finally, rotation (and mud flow) is resumed. Notice that the stand pipe pressure (SPPA) also drops during the stand change operations.

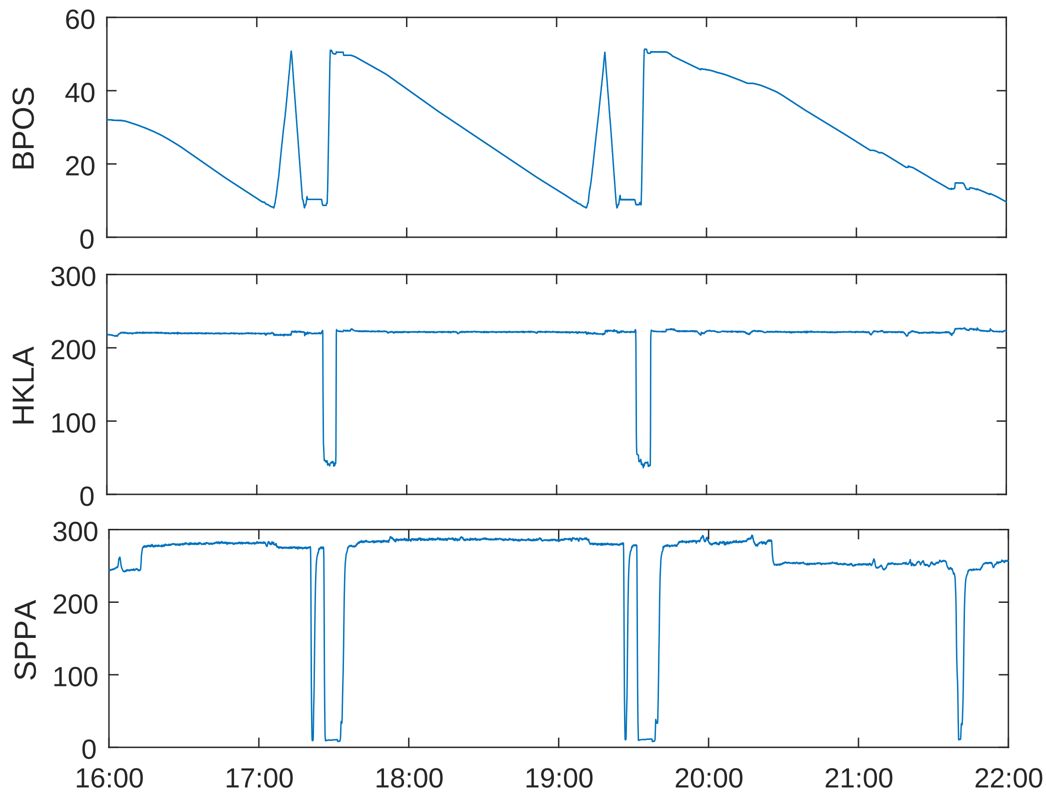

Figure 2: Drilling example 1. From top to bottom: BPOS, HKLA, SPPA.

3. Data-driven characterization of the stuck-pipe conditions

Sticking occurs when the drillstring can be neither rotated nor moved along the axis of the wellbore. A pipe is considered stuck if it cannot be freed from the hole without damaging the pipe and without exceeding the drilling rig's maximum allowed hook load. Pipe sticking typically occurs due to differential pressure issues or mechanical blocking. In the first case, if the pressure in the annulus exceeds that in the formation being drilled, the drillstring is pulled against the wall and held against it. A relatively low differential pressure applied over a large working area may be sufficient to stick the pipe. In high-angle and horizontal wells, gravitational force also plays a role in extending the contact between the drillstring and the formation.

The notion of mechanical sticking describes the limiting or prevention of motion of the drillstring for other reasons, *e.g.* the presence of junk in the hole, wellbore geometry anomalies, the formation of packoff from poor hole-cleaning (the cuttings settle and eventually pack around the drill string), unfavorable properties of the drilled formation, keyseats.[3]

Early signals of poor hole-cleaning conditions can be found in an erratic torque (the string is repeatedly getting stuck in the cuttings, wound up and spun free), an unexplained increase in the bottom hole pressure (which may be associated to a tight spot with packings causing flow restrictions further up the annulus), or an unexpected hook load (if the drill string rests on a tight packing, the hook load is less than expected) (Nybø, 2009). Preventing stuck pipes may require careful monitoring of early warning signs, such as increases in torque and drag, excessive loading of cuttings, tight spots while tripping, loss of circulation while drilling.

In terms of the signals available in the mudlog the following phenomena – though not necessarily all at the same time– are often observed in connection with a sticking event:

1. BPOS presents anomalies with respect to its previous pattern.
2. DBTM is either constant or displays high frequency oscillations of small amplitude (due to the operator's attempt to disengage the drill string).
3. HKLA increases and/or oscillates.
4. RPMA decreases or goes to 0 (it displays downward spikes).
5. TQA increases (and displays upward spikes).
6. SPPA increases (due to the formation of some obstacle to the mud flow).
7. In normal conditions of the well MFOA = MFIA. When there is a sticking event, MFOA can decrease to zero. The same situation happens also in case of a circulation loss.
8. If in drilling, WOBA increases before the sticking, at the sticking depth.

[3] A keyseat is a small-diameter channel worn into the side of a larger diameter wellbore, where the drillstring may fit too tightly and eventually get stuck.

Not all these phenomena appear together in sticking events, at least to the recollection of the authors, but at least three typical patterns are observed, as will be discussed in detail in the next section. The first pattern explains the physical phenomenon of the sticking regarding the impairment of motion along the well main axis and it is therefore associated with the depth variables: DBTM and BPOS are either constant or have small oscillations, and HKLA oscillates following BPOS (since the pipe is stuck, acting on BPOS reflects directly on the load sensed on the hook). The second pattern can be used to detect difficulties in the rotational motion of the drill string and is found in drilling/reaming/backreaming operations (rotation must be on): TQA increases abnormally (possibly with spikes) while RPMA falls. Notice that RPMA can also be zero for legitimate reasons (simply because the rotation is set off). At the same time, TQA spikes associated with the mounting of stands should be discarded. A third important pattern related to sticking regards the pressure balance in the wellbore and involves the pressure and pump flow variables. In particular, unexpected surges in SPPA, which are not justified by variations of the mud flow, may indicate the formation of a pack off due to poor hole cleaning, a condition that may degenerate into a sticking.

The following subsections illustrate some typical patterns of the mudlog variables related to sticking events that occurred while drilling the same well.

3.1. Sticking 1

A first example of mudlog signals recorded during a sticking event is shown in Figure 3. This event occurred during a drilling operation at a depth of 4670 m. More precisely, the sticking actually happens as the bit travels upwards along the free hole while reaming up the stand before the next connection. The rotation stops a few minutes after the beginning of the backreaming operation (9:33 and 9:35), with corresponding upward spikes of TQA, and the sticking occurs. The operator applied some additional pull to the drillstring to stretch it with the aim of unblocking it (see oscillations of $\pm$ 20 tons on HKLA from 9:33 onwards), but it required several attempts to finally free the string.

3.2. Sticking 2

A second sticking example is shown in Figure 4. This event occurred during a tripping out operation about 200 m above the borehole depth. A tight spot was observed at 4623 m after 20:47 with the string unable to move up/down (the BPOS cannot go over 30 m) and to rotate either. The operator tried to vary HKLA by $\pm$ 20 tons but the string was unable to move vertically. A rotation was also applied simultaneously in an attempt to clean the hole (the SPPA pressure was also increased for the same purpose), initially resulting in very large TQA values. The action was successful as the torque was progressively reduced and normal rotation conditions were resumed at some point and the operator was able to move the string at least downwards. After a few more pulls, the string was finally freed and the tripping was resumed.

This case shows that the spikes in TQA are not always a direct marker to identify stuck pipes, since the problem begins here with a drill bit unable to rotate following a time window where TQA is zero due to an explicit drilling policy (a tripping operation is going on, with rotation off). One cannot identify the beginning of the sticking by looking (only) at TQA. The problem is more clearly emphasized when looking at the depth variables: BPOS cannot go all the way up and HKLA goes beyond the baseline level. Actually, one can observe a high correlation between BPOS and HKLA at high frequency during the event (when the pipe is stuck, acting on the block position applies a corresponding traction/compression on the pipe, which directly reflects in the variations of HKLA), whereas the two variables are essentially uncorrelated in normal tripping operations.

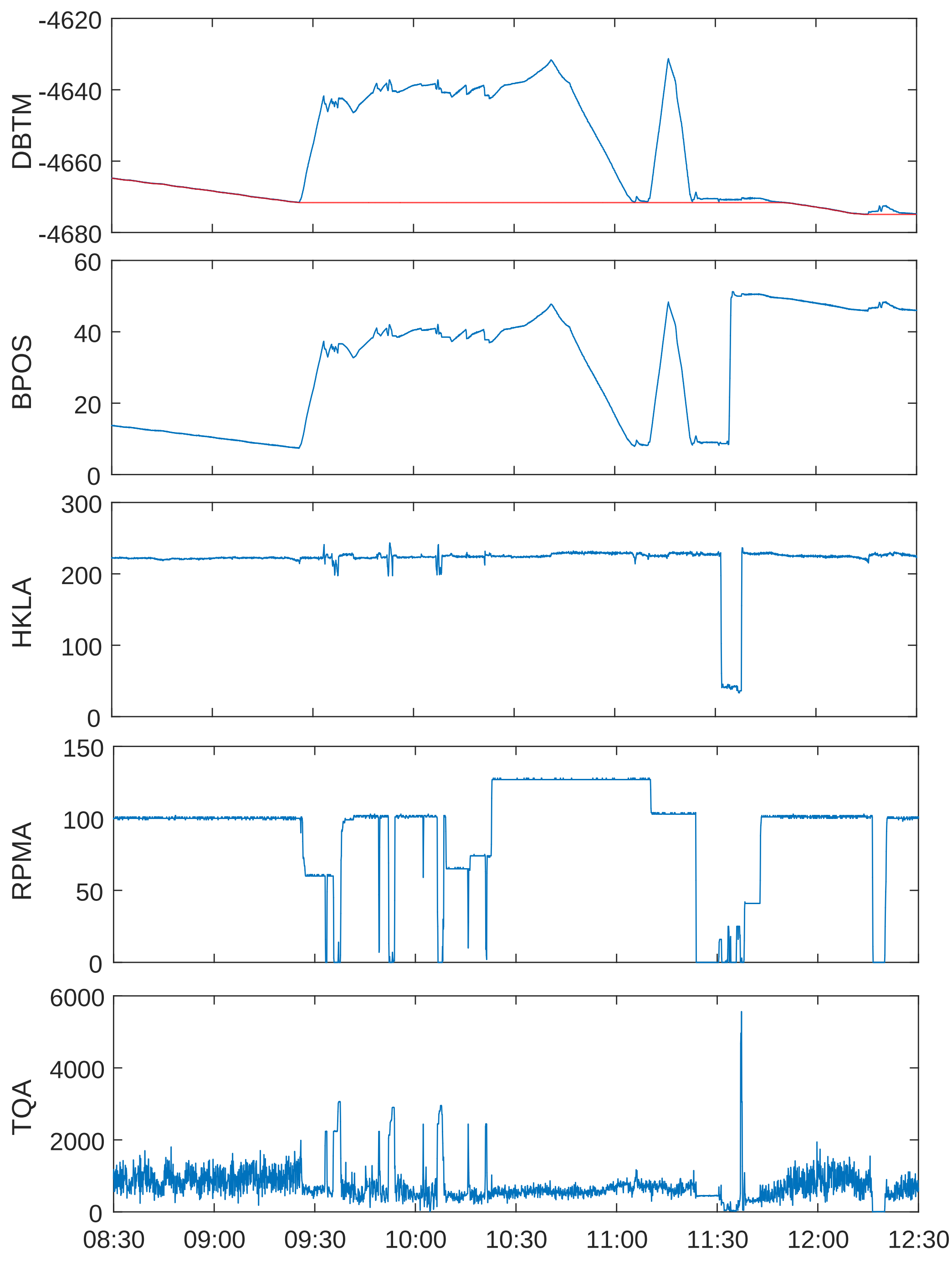

Figure 3: Sticking 1. From top to bottom: DBTM (blue) and DMEA (red), BPOS, HKLA, RPMA, TQA.

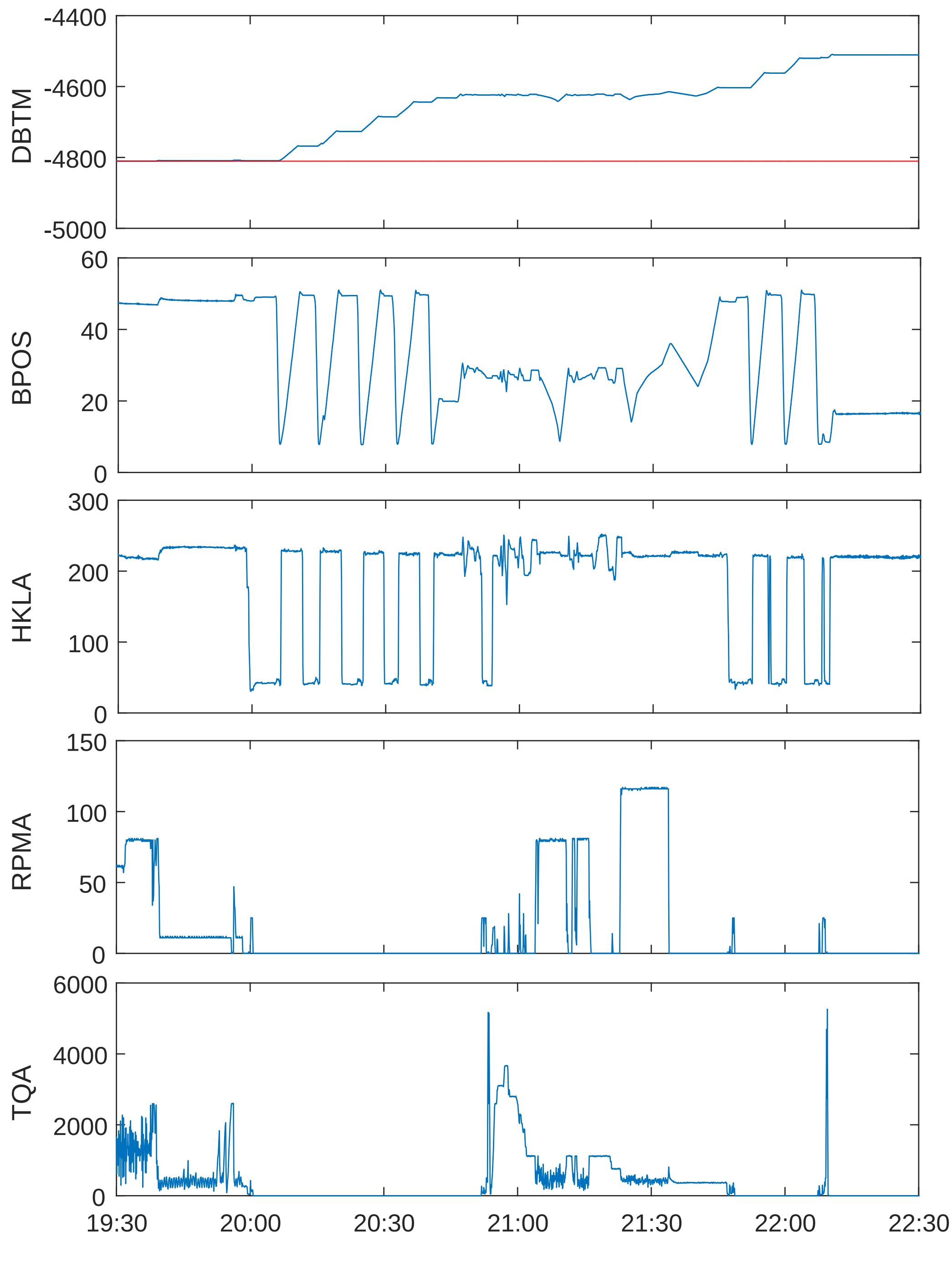

Figure 4: Sticking 2. From top to bottom: DBTM (blue) and DMEA (red), BPOS, HKLA, RPMA, TQA.

4. Design of a sticking indicator based on the BPOS and HKLA signals

A closer look at the dynamics of BPOS and HKLA during sticking events (see Figures 5-6) shows that there are large time portions in which the BPOS and HKLA dynamics are extremely well correlated in the high-frequency dynamics. Indeed, if the motion along the borehole axis is impaired and the drillstring is blocked, each pull exerted by moving the block upwards produces a corresponding increase in the load measured at the hook and vice versa. On the other hand, when the drillstring is free, the upwards and downwards motions of the block do not significantly affect the hook load.

This behavior of the BPOS and HKLA signals motivates the use of a correlation index for the detection and, possibly, the anticipation of the sticking, denoted D_{lin} in the following. Indeed, in difficult spots, the string may get near to blocking conditions, with analogous results on BPOS and HKLA – albeit to a smaller extent. The intensity and frequency of these indicators can be used as anticipatory signals of the sticking.

The high-frequency behavior of the BPOS and HKLA signals is captured by taking the differences with respect to a smoothed version of the same signals obtained by a classical rolling median approach. More precisely, a baseline of each signal is computed with a rolling median with a 35-second window, resulting in $BPOS_{median}$ and $HKLA_{median}$ (this window length was found to be a good trade-off between filtering the noise in the data and not concealing important events). Then, the high-frequency components are computed as differences between each signal and the respective baseline, yielding $BPOS_{diff} = BPOS_{raw} - BPOS_{median}$ and $HKLA_{diff} = HKLA_{raw} - HKLA_{median}$. Then, the correlation between these two signals is finally calculated with a rolling window approach, *e.g.* over rolling windows of 60 samples (5 minutes). In other words, a value of the index is computed for each sample, considering the previous 5 minutes of data (because of this, the algorithm requires an initial startup time of 5 minutes to gather sufficient data for the computation). Before calculating the correlation, the $HKLA_{diff}$ signal is linearly detrended in the 5-minute window to avoid capturing unwanted low-frequency correlations.

The raw correlation signal takes a relatively high value at sticking events, but also generates a significant number of spurious events (see Figure 7, bottom). These false alarms are critical since they may eventually cause the operator to distrust and neglect the messages provided by the indicator.

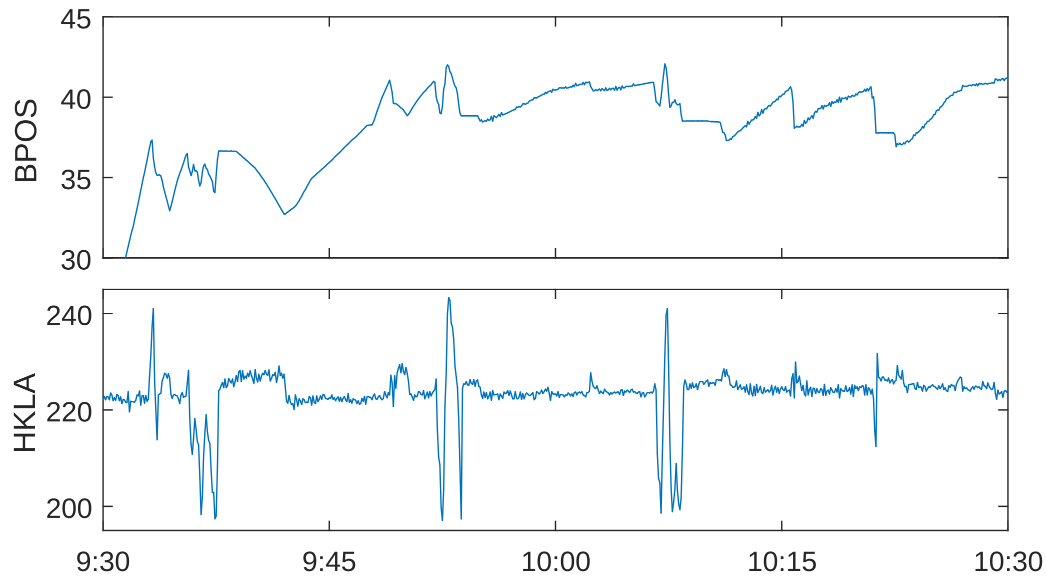

Figure 5: Sticking 1: detail of the BPOS and HKLA signals.

They must indeed be prefiltered for a successful application of the index.

These false alarms are mostly related to stand change operations (especially during tripping). Various data-driven rules can be employed to detect stand changes, although the problem is far from trivial since such operations display a relatively large variety of patterns. Since the drillstring is clamped during a stand change, with a significant reduction in the load perceived at the hook, a simple conservative rule is to remove the samples associated with a HKLA value below a given threshold (depending on the length and weight of the drillstring). This removes the data corresponding to stand changes as well as some data portions corresponding to tripping operations, when only a small portion of the drillstring is inserted in the hole. This is not necessarily a problem, given that the initial part of the borehole is cased and no sticking problem is expected to occur inside the casing. For example, in the considered dataset, the HKLA is generally over $HKLA_0 = 200$ tons, and using a threshold of *e.g.* $HKLA \leq 0.75\, HKLA_0$ results into an effective elimination of all problematic data. A good rule of thumb for sizing this threshold would be to use as $HKLA_0$ the hook load value corresponding to the drillstring which exactly covers the length of the cased part of the borehole, if this information is available.

To facilitate the interpretation of the proposed indicator, the correlation

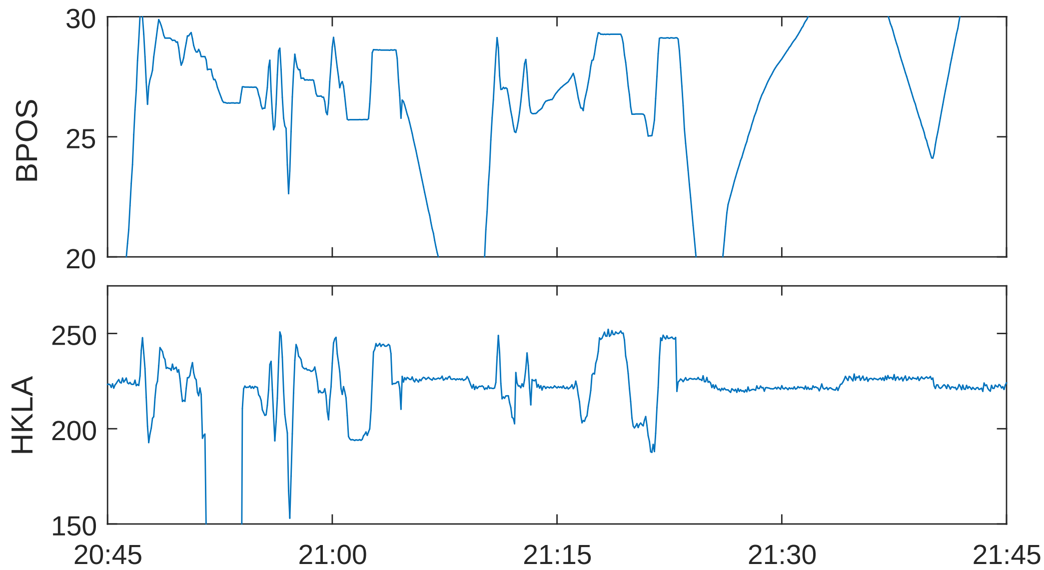

Figure 6: Sticking 2: detail of the BPOS and HKLA signals.

values (ranging up to 1) can be discretized in various alarm levels. In the following, we simply discarded all index values lower than 0.25 (as in normal operation the values never exceed this value) and issued an alarm otherwise.

Algorithm 1 provides a pseudo-code of the procedure that calculates the D_{lin} index. The data must be pre-filtered to remove stand change operations, prior to applying Algorithm 1. Function $median(x, W)$ calculates a centered moving median of length W over signal x. Function $detrend(\cdot)$ removes the linear trend from the input signal x. Finally, function $corr(x, y)$ computes the correlation between x and y. In the experimental analysis, the design parameters W (rolling median window) and L (correlation window) are set to 35 and 60 samples, respectively.

Figure 7 (bottom) shows the raw correlation signal before the stand-change pre-filtering (blue), and points out the correlation values higher than 0.25 (red). As can be seen from the figure, many false alarms are issued in this way, which can be mostly ascribed to stand change operations. The number of these false alarms is greatly reduced by applying the aforementioned pre-filtering prior to the calculation of the correlation, as can be seen in Figure 7 (bottom), by comparing the magenta line (corresponding to D_{lin}) with the red one.

The remaining alarms are associated with the documented stickings and

Algorithm 1 D_{lin} index

Inputs : $BPOS$, $HKLA$, W, L
Output : D_{lin}
$BPOS_{rm} = median(BPOS, W)$;
$HKLA_{rm} = median(HKLA, W)$;
$T = length(BPOS)$;
for $k = 1 : T$ **do**
    $BPOS_{diff}(k) = BPOS(k) - BPOS_{rm}(k)$;
    $HKLA_{diff}(k) = HKLA(k) - HKLA_{rm}(k)$;
end for
for $k = L : T$ **do**
    $c(k) = corr(BPOS_{diff}(k-L+1 : k), detrend(HKLA_{diff}(k-L+1 : k)))$;

    if $c(k) \geq 0.25$ **then**
        $D_{lin}(k) = 1$;
    else
        $D_{lin}(k) = 0$;
    end if
end for

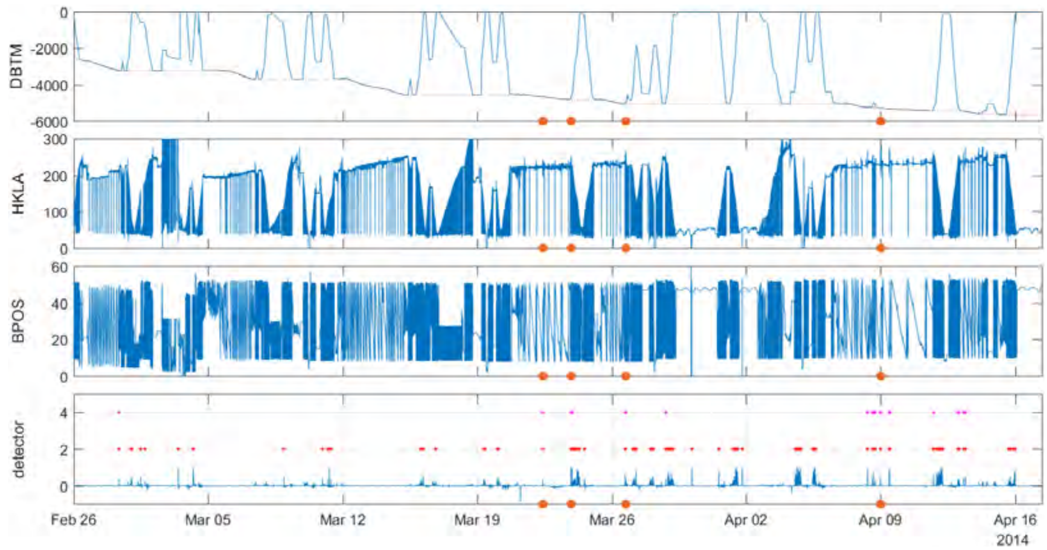

Figure 7: Detector D_{lin} as a function of time. From top to bottom: DBTM (blue) and DMEA (red), HKLA, BPOS, detector (raw correlation in blue, correlation values higher than 0.25 in red, D_{lin} in magenta). The orange circles identify the locations of the documented stickings.

other minor non-catastrophic events. The latter are often associated with difficult spots encountered during the process and deemed not severe enough to be officially reported as stickings in the timelog. This indicates that the information provided by D_{lin} could possibly be used as an anticipation for drilling problems. Notice in particular the frequency of such events just before the fourth sticking, which can be employed to anticipate it.

Another interesting assessment of the sticking indicator can be carried out by reordering the data over the depth variable (DBTM), as shown in Figure 8. A careful inspection of the figure indicates a precise depth localization of the problematic portions of the wellbore.

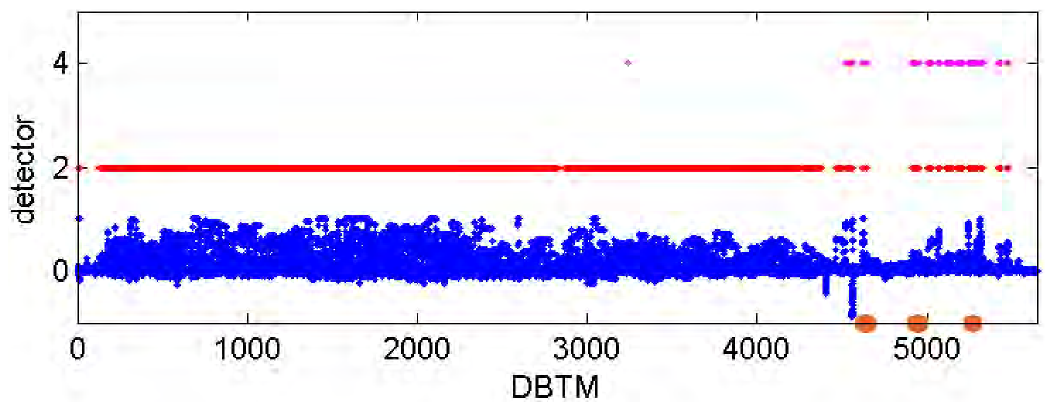

Figure 8: Detector D_{lin} as a function of depth: raw correlation (blue), correlation values higher than 0.25 (red), D_{lin} (magenta). The orange circles identify the locations of the documented stickings.

5. Design of a sticking indicator based on the TQA and RPMA signals

The second physical phenomenon we considered is related to the rotational movement of the drillstring. Intuitively, when resistance to rotation is encountered, the RPMA signal is expected to drop and, at the same time, a large value of TQA will be experienced. This phenomenon is emphasized during stickings where rotation can be completely blocked. As done in the previous section, let's take a closer look at the TQA and RPMA signals during sticking events (see Figure 9-10). As expected in both cases there are various time intervals in which the RPMA signal drops and, at the same time, there is a surge in TQA, which otherwise has a relatively low value. Notice that the duration of such time intervals can vary quite a lot: in the first sticking the events are relatively short, while a larger period is observed in the second case around 21:00. Apparently, in this case, the operator applied a sustained rotation to the drillstring to wear out the resistance (indeed, the TQA slowly drops to lower values). Notice that afterward (slightly after 21:00) the operator has inserted a limiter at the maximum torque (see the saturations at 1000).

The proposed index, denoted D_{rot} in the sequel, is essentially based on the ratio between TQA and RPMA, which takes large values when the former variable is large while RPMA is small, a condition typically observed in tight

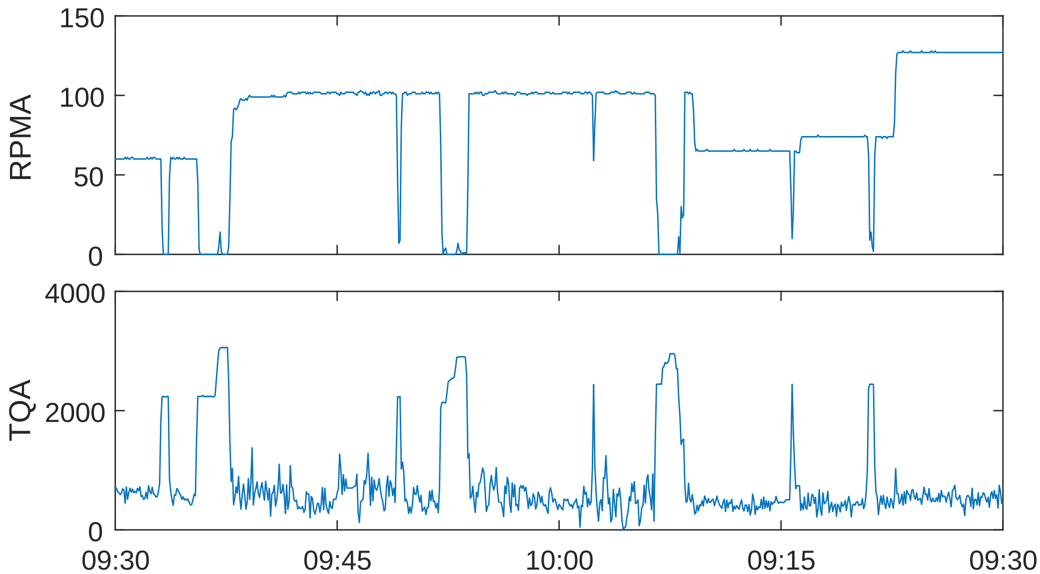

Figure 9: Sticking 1: detail of the TQA and RPMA signals.

spots and stickings.[4] To avoid a division by zero, RPMA is saturated from below by a small positive value. Notice that RPMA can be zero for legitimate reasons as well (when the operator switches off the rotation), but in this case TQA is zero as well (and consequently also D_{rot}). Conversely, the TQA can have large spikes without this representing a problem, as it happens in the connection/disconnection phase during stand changes, when the new stand is screwed upon the drillstring. For these reasons, as done for D_{lin}, the stand change operations must be filtered before the index calculation.

The procedure that calculates the D_{rot} index is summarized in the pseudocode of Algorithm 2. As before, the data must be pre-filtered to remove stand change operations. Here, $W = 20$ is the window length over which the index is calculated, and the threshold for issuing an alarm is set to $A = 18$ (*i.e.*, at least 18 samples out of 20 consecutive ones must have a large $\frac{TQA}{RPMA}$ ratio to set off the indicator).

The ratio threshold has been set based on a statistical analysis of the data in the presence and absence of drilling problems, comparing the data

[4]For proper generalization of this index to other well datasets, normalization is in order for both variables.

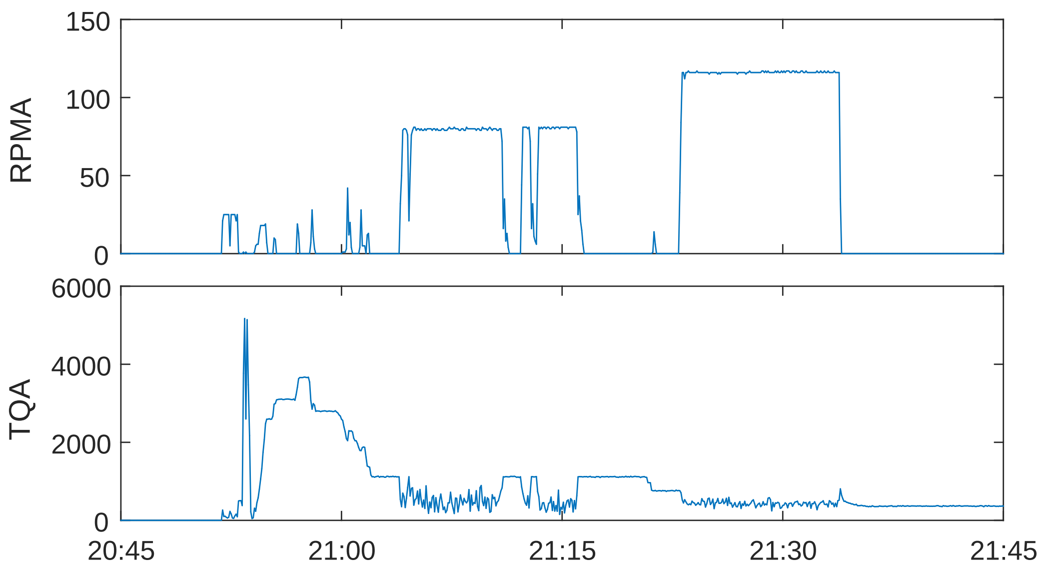

Figure 10: Sticking 2: detail of the TQA and RPMA signals.

collected during normal activities to those associated to stuck-pipe events. The window length has been empirically determined to provide sufficient noise filtering while preserving the important fluctuations of the signal.

Figures 11-12 report the results obtained with the constructed detector: D_{rot} captures all the documented stickings and, at the same time, yields a very small number of false positives. Notice that most of the added alarms are in the deepest portion of the borehole (where several problems related to circulation losses are noted as well), in agreement with the BPOS-HKLA detectors.

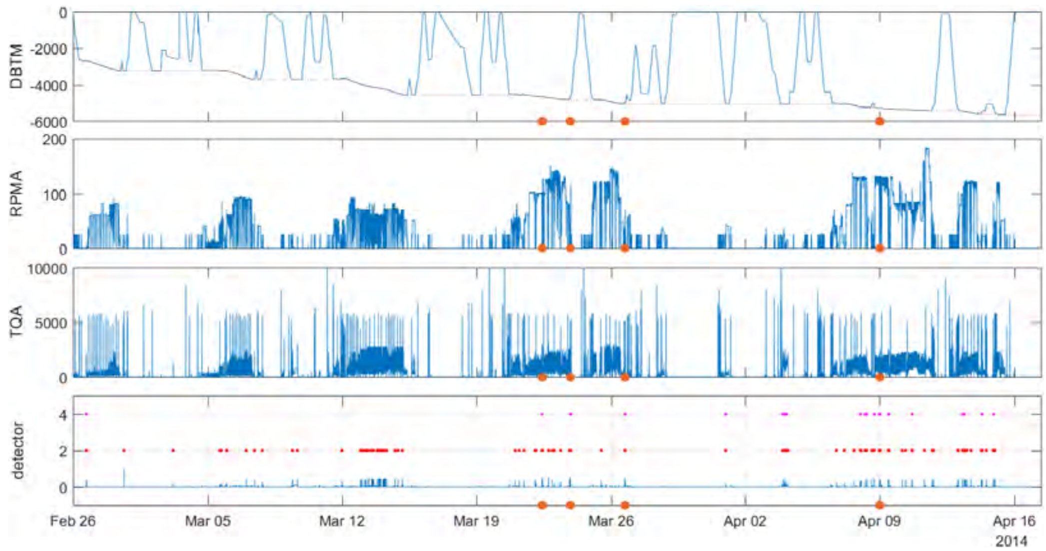

Figure 11: Detector D_{rot} as a function of time. From top to bottom: DBTM (blue) and DMEA (red), RPMA, TQA, detector (normalized raw ratio in blue, rolling window count of over-threshold samples in red, D_{rot} in magenta). The orange circles identify the locations of the documented stickings.

Algorithm 2 D_{rot} index

Inputs : TQA, $RPMA$, W, A
Output : D_{rot}
$T = length(TQA)$;
for $k = 1 : T$ **do**
  if $\frac{TQA(k)}{\max(RPMA(k),1)} \geq 1000$ **then**
    $R(k) = 1$
  else
    $R(k) = 0$;
  end if
end for
for $k = W : T$ **do**
  if $sum(R(k - W + 1 : k)) \geq A$ **then**
    $D_{rot}(k) = 1$;
  else
    $D_{rot}(k) = 0$;
  end if
end for

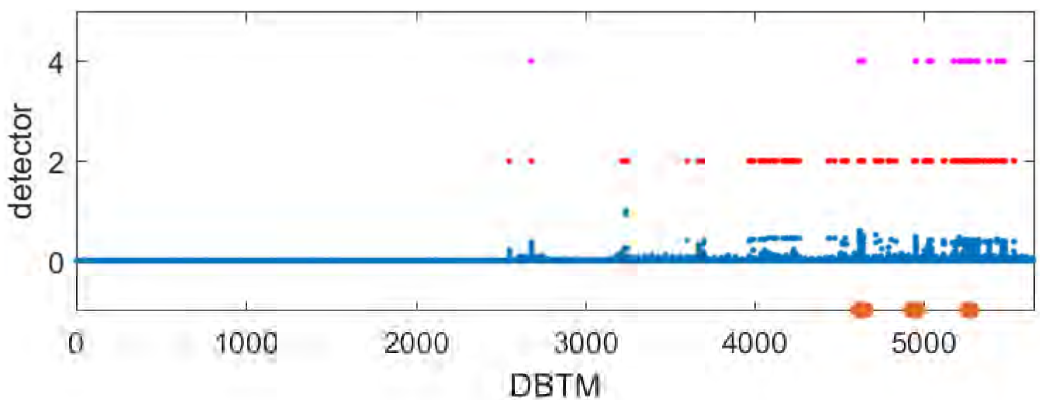

Figure 12: Detector D_{rot} as a function of depth: normalized raw ratio (blue), rolling window count of over-threshold samples (red), D_{rot} (magenta). The orange circles identify the locations of the documented stickings.

6. Design of a sticking indicator based on the SPMT and SPPA signals

The role of the drilling mud in maintaining the borehole stability, by balancing the pore pressure with its hydrostatic pressure, is crucial in the drilling process. If the hydrostatic pressure of the mud is insufficient, a blow out may occur, whereas if excessively large it may cause fractures in the formation, with consequent mud losses. Monitoring of the mud flow through MFIA and MFOA is not practicable in our case, due to the unreliability of the latter signal. Therefore, only the SPPA signal can be used for pressure monitoring.

In this respect, we observed that unexpected surges of the standpipe pressure can also be connected to poor cleaning conditions, leading to a formation of a pack off of the cuttings, which in turn causes an obstacle to the BHA motion. To establish whether an increase in SPPA is, instead, associated with a deliberate action by the operator, one can check whether the total pump stroke rate SPMT has changed throughout the surge.

Accordingly, we define a third index, denoted as D_{press}, which evaluates the variability of the SPPA on a rolling window, if SPMT is non zero and (practically) constant. The index is calculated according to Algorithm 3. As before, the data must be pre-filtered to remove stand change operations. The standard deviation of SPPA in a rolling window is used as a raw indicator, provided SPMT is constant (but not zero) in the window. Here, $W = 100$ is the window length over which the index is calculated, and the threshold for issuing an alarm is set to $A = 10$. The condition $SPPA(k) > SPPA_{rm}(k)+5$ is designed to detect a peak in SPPA. Functions $mean(x)$ and $std(x)$ calculate the mean and standard deviation of vector x, respectively.

Figures 13-14 show the performance of the proposed detector D_{press}. Apparently, alarms are issued at the locations of the documented stickings, as well as in a few other locations, mostly in the deepest section of the borehole.

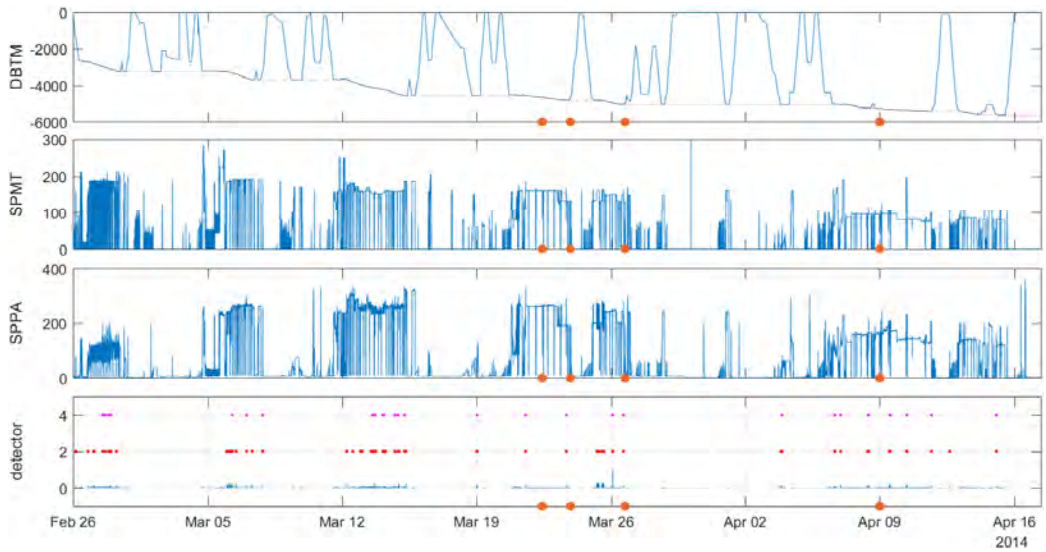

Figure 13: Detector D_{press} as a function of time. From top to bottom: DBTM (blue) and DMEA (red), SPMT, SPPA, detector (normalized raw ratio in blue, over-threshold samples in red, D_{press} in magenta). The orange circles identify the locations of the documented stickings.

Algorithm 3 D_{press} index

Inputs : $SPMT$, $SPPA$, W, A
Output : D_{press}
$SPPA_{rm} = median(SPPA, W)$;
$T = length(SPMT)$;
for $k = W : T$ **do**
  if $std(SPMT(k-W+1:k)) \leq 1 \wedge mean(SPMT(k-W+1:k)) > 10$ **then**
    $R(k) = std(SPPA(k-W+1:k))$
  else
    $R(k) = 0$;
  end if
  if $R(k) \geq A \wedge SPPA(k) > SPPA_{rm}(k) + 5$ **then**
    $D_{press}(k) = 1$;
  else
    $D_{press}(k) = 0$;
  end if
end for

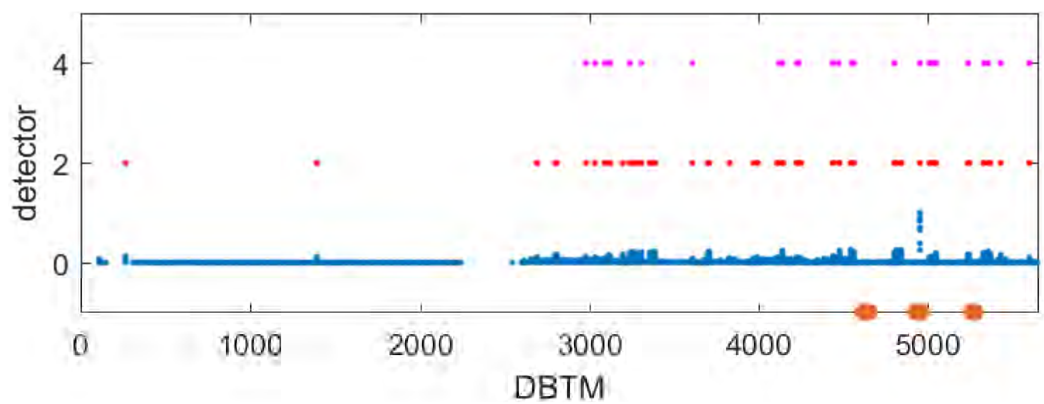

Figure 14: Detector D_{press} as a function of depth: normalized raw ratio (blue), over-threshold samples in red (red), D_{press} (magenta). The orange circles identify the locations of the documented stickings.

7. The wellbore status model

The three proposed detectors can be used in the post-processing of the drilling data to check the locations of the wellbore problems, but –more importantly– they can also be employed during drilling to point out both minor and major drilling problems (with an attached direct physical interpretation), the former representing also possible precursors of stickings. In this section, we discuss the construction of a prediction model based on these detectors.

The basic idea is to use the available drilling data to correlate the detectors (as well as raw mudlog signals) to an alarm signal that is artificially constructed by assigning the largest value in correspondence of each documented sticking, and a progressively lower value going back in time and upwards in depth. Indeed, we would like an alarm to be issued (and its level increased) as a sticking approaches, either in time or in depth.

Both input and output data are aggregated in depth-based 4 m bins and averaged, prior to training, to reduce the variability and noise in the data. Then, at each time an input/output variable is characterized by a vector of values (one value for each depth bin), resulting in a tabular structure of the dataset. The data are divided into a training and a test set, the former to be used to train the model and the second to assess its performance. The model can be trained using any standard regression algorithm on the training set. In this study, we illustrate the results obtained with the Extra Trees method (Geurts et al., 2006). Finally, one can obtain the predictions for the test set by applying the obtained model on the set of features at the current depth/time location.

In particular, to test the model performance along a specific phase of the drilling process (between two consecutive casing operations) of a well, we can use as training set all the data pertaining to the other available wells, together with the data of the previous drilling phases of the same well (obtained before the last casing operation). The results take the form of an alarm vector, which has a value for each depth bin, indicating the alarm level for that depth. Over time the input features at a specific depth change as new data are collected in the same depth bin. Correspondingly, the alarm level associated with a specific depth bin can increase, because more critical conditions are encountered, or decrease due to the operator's recovery actions (*e.g.*, reaming and backreaming). By monitoring such alarm vector, the operator can ultimately anticipate an impending sticking and take appropriate action to try to avoid it.

Figure 15 shows a pictorial representation of the outcome of the prediction model taken at three subsequent moments during a drilling phase that ended in a particularly severe stuck-pipe event. As the drilling proceeds, the model (trained on other wells and on the previous phase of the same well) initially indicates a relatively healthy status of the wellbore (left picture), until reaching the 200th bin (*i.e.*, 800 m in depth). Several depth bins are marked with a high level of risk (middle picture). Although the subsequent actions were able to modify only slightly the level of risk of the depth bins in this area, the drilling was resumed (the bit goes further down to the 240th bin) leaving behind a high-risk area. This turned out to be a bad choice, as a stuck pipe incident occurred when passing again through that area in tripping out. Specifically, the sticking occurs when the bit is a few bins below the critical region, which is compatible with the position of the largest elements of the drillstring with respect to the bit. By properly reworking and consolidating the critical area before resuming the drilling, the sticking could have possibly been avoided.

A correct assessment of the model is difficult to carry out, since a fair experiment, without the human-in-the-loop, is unfeasible. Indeed, a drilling problem may or may not degenerate into a full stuck-pipe event, depending on the driller's reactivity and drilling strategy. Thus, identical conditions may lead to a fault or not, which obviously thwarts the design of a prediction model for this application. This is ultimately the reason why we actually focused on detecting the conditions that may lead to a fault, rather than predicting the fault itself. More precisely, the model evaluates the level of risk of incurring in a stuck-pipe at every depth level of the borehole and at every time instant. In this sense, the model does not give false alarms, in that all the alarms it issues are caused by (small or big) physical drilling problems. The model can be used in a predictive fashion by the driller, as it indicates an increasing level of alarm as a sticking condition is approached.

A preliminary analysis was carried out to assess the recall properties of the model, *i.e.* its ability to detect as many stickings as possible, out of the documented ones. Five wells were considered in the analysis with a total of 11 stuck-pipe events. Six of these events could have been anticipated using the proposed model, resulting in a recall rate of approximately 55%. The results are far from conclusive, as the available data-set is small, but this figure is promising, considering that stuck-pipes are relatively rare events. An analysis of the results also reveals that the model was able to anticipate all stickings that occurred during tripping-out phases, indicating that the physical evidence obtained from previous passings through the involved portions of the borehole was fruitfully exploited.

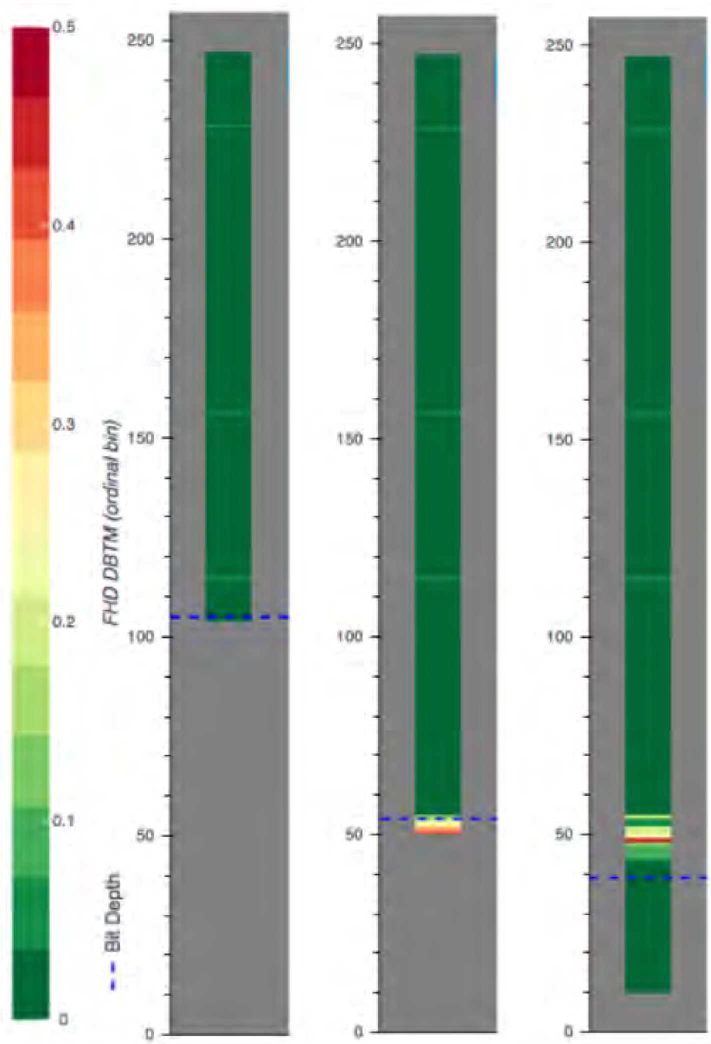

Figure 15: Screenshots of the web application showing the predicted status of the wellbore at three subsequent timesteps.

8. Conclusion

Three different indicators were designed based on the mudlog data, with the aim of capturing three different physical phenomena associated with the insurgence of a sticking. The first is designed to spot difficulties in the linear motion of the drillstring, whereas the second aims at recognizing rotational issues. The third indicator detects unexpected standpipe pressure surges.

All three indicators provide valuable information both during and after drilling, in the data assessment phase. During drilling operations, careful monitoring of these indicators can emphasize both minor and major drilling issues and allow the drilling operator to take appropriate actions. An *a posteriori* inspection can help correct and integrate the manual timelog filled by the drilling crew. This post-processing is particularly useful for providing a reliable ground truth for machine learning models that aim at predicting the mentioned drilling problems.

A statistical model was also developed that correlates the three indicators as well as other features extracted from the mudlog data with an artificial target signal, which reproduces an increasing alarm level as a sticking event approaches. Preliminary results indicate that this model can provide useful information to the drilling crew, under which timely actions can be taken to mitigate and sometimes avoid drilling issues.

Acknowledgment

This work is part of an ongoing project in ENI concerning big data analytics for NPT (non-productive time) prediction and operational efficiency.

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